Practical Machine Learning Course Project

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# Instructions

One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it. In this project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants.

### Review criteria

#### What you should submit

**The goal of your project is to predict the manner in which they did the exercise. This is the "classe" variable in the training set. You may use any of the other variables to predict with. You should create a report describing:**

* **How you built your model**
* **How you used cross validation**
* **What you think the expected out of sample error is**
* **Why you made the choices you did**

**You will also use your prediction model to predict 20 different test cases.**

#### Peer Review Portion

Your submission for the Peer Review portion should consist of a link to a Github repo with your R markdown and compiled HTML file describing your analysis. Please constrain the text of the writeup to < 2000 words and the number of figures to be less than 5. It will make it easier for the graders if you submit a repo with a gh-pages branch so the HTML page can be viewed online (and you always want to make it easy on graders :-). Course Project Prediction Quiz Portion

Apply your machine learning algorithm to the 20 test cases available in the test data above and submit your predictions in appropriate format to the Course Project Prediction Quiz for automated grading.

#### Reproducibility

Due to security concerns with the exchange of R code, your code will not be run during the evaluation by your classmates. Please be sure that if they download the repo, they will be able to view the compiled HTML version of your analysis.

### Prediction Assignment Writeup

#### Background

Using devices such as Jawbone Up, Nike FuelBand, and Fitbit it is now possible to collect a large amount of data about personal activity relatively inexpensively. These type of devices are part of the quantified self movement – a group of enthusiasts who take measurements about themselves regularly to improve their health, to find patterns in their behavior, or because they are tech geeks. One thing that people regularly do is quantify how much of a particular activity they do, but they rarely quantify how well they do it. In this project, your goal will be to use data from accelerometers on the belt, forearm, arm, and dumbell of 6 participants. They were asked to perform barbell lifts correctly and incorrectly in 5 different ways. More information is available from the website here: <http://groupware.les.inf.puc-rio.br/har> (see the section on the Weight Lifting Exercise Dataset). Data

The training data for this project are available here:

<https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv>

The test data are available here:

<https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv>

The data for this project come from this source: <http://groupware.les.inf.puc-rio.br/har>. If you use the document you create for this class for any purpose please cite them as they have been very generous in allowing their data to be used for this kind of assignment.

# Input Data

I will load the R packages needed for analysis and download the training and testing data sets.

# load the required packages  
library(caret); library(rattle); library(rpart); library(rpart.plot)  
library(randomForest); library(repmis); library(e1071)

# import the data from the URLs  
trainurl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-training.csv"  
testurl <- "https://d396qusza40orc.cloudfront.net/predmachlearn/pml-testing.csv"  
training <- source\_data(trainurl, na.strings = c("NA", "#DIV/0!", ""), header = TRUE)  
testing <- source\_data(testurl, na.strings = c("NA", "#DIV/0!", ""), header = TRUE)

dim(training)

[1] 19622 160

dim(testing)

[1] 20 160

The training dataset has 19622 observations and 160 variables, and the testing data set contains 20 observations and the same 160 variables.

### Data Cleaning

I will now delete columns (predictors) of the training set that contain any missing values.

training <- training[, colSums(is.na(training)) == 0]  
testing <- testing[, colSums(is.na(testing)) == 0]

names(training)

[1] "V1" "user\_name" "raw\_timestamp\_part\_1"  
 [4] "raw\_timestamp\_part\_2" "cvtd\_timestamp" "new\_window"   
 [7] "num\_window" "roll\_belt" "pitch\_belt"   
[10] "yaw\_belt" "total\_accel\_belt" "gyros\_belt\_x"   
[13] "gyros\_belt\_y" "gyros\_belt\_z" "accel\_belt\_x"   
[16] "accel\_belt\_y" "accel\_belt\_z" "magnet\_belt\_x"   
[19] "magnet\_belt\_y" "magnet\_belt\_z" "roll\_arm"   
[22] "pitch\_arm" "yaw\_arm" "total\_accel\_arm"   
[25] "gyros\_arm\_x" "gyros\_arm\_y" "gyros\_arm\_z"   
[28] "accel\_arm\_x" "accel\_arm\_y" "accel\_arm\_z"   
[31] "magnet\_arm\_x" "magnet\_arm\_y" "magnet\_arm\_z"   
[34] "roll\_dumbbell" "pitch\_dumbbell" "yaw\_dumbbell"   
[37] "total\_accel\_dumbbell" "gyros\_dumbbell\_x" "gyros\_dumbbell\_y"   
[40] "gyros\_dumbbell\_z" "accel\_dumbbell\_x" "accel\_dumbbell\_y"   
[43] "accel\_dumbbell\_z" "magnet\_dumbbell\_x" "magnet\_dumbbell\_y"   
[46] "magnet\_dumbbell\_z" "roll\_forearm" "pitch\_forearm"   
[49] "yaw\_forearm" "total\_accel\_forearm" "gyros\_forearm\_x"   
[52] "gyros\_forearm\_y" "gyros\_forearm\_z" "accel\_forearm\_x"   
[55] "accel\_forearm\_y" "accel\_forearm\_z" "magnet\_forearm\_x"   
[58] "magnet\_forearm\_y" "magnet\_forearm\_z" "classe"

names(testing)

[1] "V1" "user\_name" "raw\_timestamp\_part\_1"  
 [4] "raw\_timestamp\_part\_2" "cvtd\_timestamp" "new\_window"   
 [7] "num\_window" "roll\_belt" "pitch\_belt"   
[10] "yaw\_belt" "total\_accel\_belt" "gyros\_belt\_x"   
[13] "gyros\_belt\_y" "gyros\_belt\_z" "accel\_belt\_x"   
[16] "accel\_belt\_y" "accel\_belt\_z" "magnet\_belt\_x"   
[19] "magnet\_belt\_y" "magnet\_belt\_z" "roll\_arm"   
[22] "pitch\_arm" "yaw\_arm" "total\_accel\_arm"   
[25] "gyros\_arm\_x" "gyros\_arm\_y" "gyros\_arm\_z"   
[28] "accel\_arm\_x" "accel\_arm\_y" "accel\_arm\_z"   
[31] "magnet\_arm\_x" "magnet\_arm\_y" "magnet\_arm\_z"   
[34] "roll\_dumbbell" "pitch\_dumbbell" "yaw\_dumbbell"   
[37] "total\_accel\_dumbbell" "gyros\_dumbbell\_x" "gyros\_dumbbell\_y"   
[40] "gyros\_dumbbell\_z" "accel\_dumbbell\_x" "accel\_dumbbell\_y"   
[43] "accel\_dumbbell\_z" "magnet\_dumbbell\_x" "magnet\_dumbbell\_y"   
[46] "magnet\_dumbbell\_z" "roll\_forearm" "pitch\_forearm"   
[49] "yaw\_forearm" "total\_accel\_forearm" "gyros\_forearm\_x"   
[52] "gyros\_forearm\_y" "gyros\_forearm\_z" "accel\_forearm\_x"   
[55] "accel\_forearm\_y" "accel\_forearm\_z" "magnet\_forearm\_x"   
[58] "magnet\_forearm\_y" "magnet\_forearm\_z" "problem\_id"

I will remove the first seven columns because these variables are irrelevant for predicting the outcome variable "classe."

training\_data <- training[, -c(1:7)]  
testing\_data <- testing[, -c(1:7)]

dim(training\_data)

[1] 19622 53

dim(testing\_data)

[1] 20 53

The cleaned data sets both have 53 columns. The first 52 variables are the same, but the last variable in the training\_data is "classe," while the last variable in the testing\_data is "problem\_id." The training\_data still has 19622 rows, and testing\_data still has 20 rows.

### Data Spliting

I will split the cleaned training set (training\_data) into a training set (train) for prediction and a validation set (validate) for computing out of sample error.

set.seed(7826)   
inTrain <- createDataPartition(training\_data$classe, p = 0.7, list = FALSE)  
train <- training\_data[inTrain, ]  
validate <- training\_data[-inTrain, ]

# Algorithm

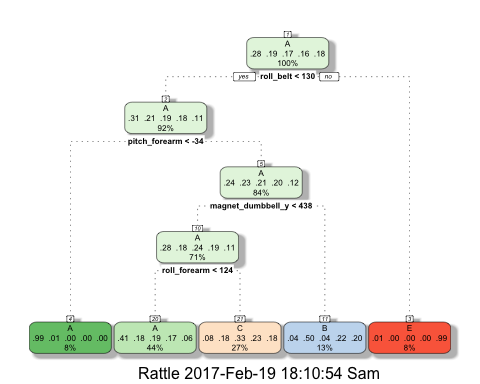
### Classification Tree

Below is a 5-fold cross validation. I chose k=5 instead of the default, k=10, to save some computing time. I did not transform any variables.

control <- trainControl(method = "cv", number = 5)  
fit\_rpart <- train(classe ~ ., data = train, method = "rpart", trControl = control)  
print(fit\_rpart, digits = 4)

CART   
  
13737 samples  
 52 predictor  
 5 classes: 'A', 'B', 'C', 'D', 'E'   
  
No pre-processing  
Resampling: Cross-Validated (5 fold)   
Summary of sample sizes: 10989, 10989, 10990, 10989, 10991   
Resampling results across tuning parameters:  
  
 cp Accuracy Kappa   
 0.03723 0.5241 0.38748  
 0.05954 0.4144 0.20668  
 0.11423 0.3482 0.09762  
  
Accuracy was used to select the optimal model using the largest value.  
The final value used for the model was cp = 0.03723.

fancyRpartPlot(fit\_rpart$finalModel)



Now I will predict the outcomes using the validation data set.

predict\_rpart <- predict(fit\_rpart, validate)  
confusion\_rpart <- confusionMatrix(validate$classe, predict\_rpart)  
confusion\_rpart

Confusion Matrix and Statistics  
  
 Reference  
Prediction A B C D E  
 A 1544 21 107 0 2  
 B 492 391 256 0 0  
 C 474 38 514 0 0  
 D 436 175 353 0 0  
 E 155 138 293 0 496  
  
Overall Statistics  
   
 Accuracy : 0.5004   
 95% CI : (0.4876, 0.5133)  
 No Information Rate : 0.5269   
 P-Value [Acc > NIR] : 1   
   
 Kappa : 0.3464   
 Mcnemar's Test P-Value : NA   
  
Statistics by Class:  
  
 Class: A Class: B Class: C Class: D Class: E  
Sensitivity 0.4979 0.51245 0.33749 NA 0.99598  
Specificity 0.9533 0.85396 0.88262 0.8362 0.89122  
Pos Pred Value 0.9223 0.34328 0.50097 NA 0.45841  
Neg Pred Value 0.6303 0.92162 0.79234 NA 0.99958  
Prevalence 0.5269 0.12965 0.25879 0.0000 0.08462  
Detection Rate 0.2624 0.06644 0.08734 0.0000 0.08428  
Detection Prevalence 0.2845 0.19354 0.17434 0.1638 0.18386  
Balanced Accuracy 0.7256 0.68321 0.61006 NA 0.94360

accuracy\_rpart <- confusion\_rpart$overall[1]  
accuracy\_rpart

Accuracy   
0.5004248

The accuracy rate is 0.5 from the confusion matrix, which means that the out of sample error rate is 0.5. The classification tree is not a very good prediction, so I will try the random forest method next.

### Random Forest

fit\_rf <- train(classe ~ ., data = train, method = "rf", trControl = control)  
print(fit\_rf, digits = 4)

Random Forest   
  
13737 samples  
 52 predictor  
 5 classes: 'A', 'B', 'C', 'D', 'E'   
  
No pre-processing  
Resampling: Cross-Validated (5 fold)   
Summary of sample sizes: 10990, 10990, 10990, 10988, 10990   
Resampling results across tuning parameters:  
  
 mtry Accuracy Kappa   
 2 0.9908 0.9884  
 27 0.9906 0.9881  
 52 0.9859 0.9821  
  
Accuracy was used to select the optimal model using the largest value.  
The final value used for the model was mtry = 2.

Now I will predict the outcomes again using the validation data set.

predict\_rf <- predict(fit\_rf, validate)  
confusion\_rf <- confusionMatrix(validate$classe, predict\_rf)  
confusion\_rf

Confusion Matrix and Statistics  
  
 Reference  
Prediction A B C D E  
 A 1673 0 0 0 1  
 B 1 1136 2 0 0  
 C 0 4 1020 2 0  
 D 0 0 21 941 2  
 E 0 0 0 2 1080  
  
Overall Statistics  
   
 Accuracy : 0.9941   
 95% CI : (0.9917, 0.9959)  
 No Information Rate : 0.2845   
 P-Value [Acc > NIR] : < 2.2e-16   
   
 Kappa : 0.9925   
 Mcnemar's Test P-Value : NA   
  
Statistics by Class:  
  
 Class: A Class: B Class: C Class: D Class: E  
Sensitivity 0.9994 0.9965 0.9779 0.9958 0.9972  
Specificity 0.9998 0.9994 0.9988 0.9953 0.9996  
Pos Pred Value 0.9994 0.9974 0.9942 0.9761 0.9982  
Neg Pred Value 0.9998 0.9992 0.9953 0.9992 0.9994  
Prevalence 0.2845 0.1937 0.1772 0.1606 0.1840  
Detection Rate 0.2843 0.1930 0.1733 0.1599 0.1835  
Detection Prevalence 0.2845 0.1935 0.1743 0.1638 0.1839  
Balanced Accuracy 0.9996 0.9979 0.9884 0.9956 0.9984

accuracy\_rf <- confusion\_rf$overall[1]  
accuracy\_rf

Accuracy   
0.9940527

The accuracy rate is 0.991, which means the out of sample error rate is 0.009. The random forest method is much better at predicting the outcome than the classification tree method.

# Evaluation

### Prediction on Testing Set

I am now ready to use the random forest method to predict the outcome variable "classe," using the testing set.

predict(fit\_rf, testing\_data)

[1] B A B A A E D B A A B C B A E E A B B B  
Levels: A B C D E